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February 9, 2021

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[1]:
```
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

# Variables
file_name = 'mba.csv'
separator = ','
random_state = 42

# Directives
%matplotlib inline
np.random.seed(random_state)
```

0. read a market basket database from the csv file provided and generate a dataframe basket of boolean values with one row per transaction and one column per distinct item of the database; the dataframe values must be True if a distinct item is contained in the transaction • the file contains one transaction per line, the first element is the number of items in the transaction, followed by the items of the transaction, and then a variable number of empty fields • the field names in the first row of the csv file are not relevant
1. ignore the transactions containing a single item (2 points)
2. the column names of the output dataframe are the distinct items (2 points)
3. show the first five rows of the output dataframe (1 point)
4. show the number of transactions and of distinct items (1 point)
5. find a value of min_support such that the apriori algorithm generates at least 8 frequent itemsets with at least 2 items (5 points) • output the result with the message below • min_support: 0.xxxx - number of itemsets with at least 2 items: nn)
6. find the minimum metric threshold such that at least 10 association rules are extracted from the frequent itemsets found (5 points) • use "confidence" as metric and output the line below: • Metric: "confidence" - min_metric: 0.xxxx - Number of rules: n
7. print the first 10 rules found, sorted by descending confidence and support (3 points)
8. plot confidence and support for all the sorted rules found (3 points)
9. scatter plot the rules by confidence and support, labelling the

points with the index value of the corresponding rule (hint https://stackoverflow.com/questions/14432557/matplotlibscatter-plot-with-different-text-at-each-data-point) (3 points)

1.1 0. read a market basket database from the csv file provided and generate a dataframe basket of boolean values with one row per transaction and one column per distinct item of the database; the dataframe values must be True if a distinct item is contained in the transaction

- *the file contains one transaction per line, the first element is the number of items in the transaction, followed by the items of the transaction, and then a variable number of empty fields*
- *the field names in the first row of the csv file are not relevant*

[2]:
```
# Open the file
file = open(file_name, mode = 'r')

# The transactions are separated by a ','
# We must also strip the '\n' at the end of the transaction
transactions = [line.strip('\n').split(separator) for line in file.readlines()]

# The first line contains field names that are not relevant, so let's skip it
transactions = transactions[1:]

# The first item in every transaction is a number of the items in the␣
 ↪transaction
# we want to use it to slice the list, removing all the empty strings and the
# number itself
for i in range(len(transactions)):

        # The end index is the number of items in the transaction
        # plus one, because we have the number itself in the slot 0
        end_index = int(transactions[i][0]) + 1
        transactions[i] = transactions[i][1:end_index]

# We now have a list of transactions with only the items in them, we can now
# use TransactionEncoder to obtain an encoded version in boolean form
encoder = TransactionEncoder()
encoded_transactions = encoder.fit_transform(transactions)

# We can now put the encoded transactions in a dataframe
basket = pd.DataFrame(encoded_transactions)
```

1.2 1. ignore the transactions containing a single item (2 points)

[3]:
```
single_item_transactions = []

# Iterate on all transactions
for index, transaction in basket.iterrows():

    # If there is just one "True" value
    if np.count_nonzero(transaction) == 1:

        # Save the index of the transaction
        single_item_transactions.append(index)

# We can now drop those transactions from the dataframe
basket.drop(index = single_item_transactions, axis = 0, inplace = True)
```

1.3 2. the column names of the output dataframe are the distinct items (2 points)

[4]:
```
basket.columns = encoder.columns_
```

1.4 3. show the first five rows of the output dataframe (1 point)

[5]:
```
basket.head()
```

[5]:

	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	\
0	False	False	False	False	
1	False	False	False	False	
3	False	False	False	False	
4	False	False	False	False	
5	False	False	True	False	

	baby cosmetics	baby food	bags	baking powder	bathroom cleaner	beef	\
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
5	False	False	False	False	False	False	

	…	turkey	vinegar	waffles	whipped/sour cream	whisky	white bread	\
0	…	False	False	False	False	False	False	
1	…	False	False	False	False	False	False	
3	…	False	False	False	False	False	False	
4	…	False	False	False	False	False	False	
5	…	False	False	False	False	False	False	

	white wine	whole milk	yogurt	zwieback

```
0       False       False   False     False
1       False       False    True     False
3       False       False    True     False
4       False        True   False     False
5       False        True    True     False

[5 rows x 169 columns]
```

1.5 4. show the number of transactions and of distinct items (1 point)

[6]:
```
print(f"There are {basket.shape[0]} transactions and {basket.shape[1]} distinct␣
↪items")
```

```
There are 7676 transactions and 169 distinct items
```

1.6 5. find a value of min_support such that the apriori algorithm generates at least 8 frequent itemsets with at least 2 items (5 points)

- *output the result with the message below*
- *min_support: 0.xxxx - number of itemsets with at least 2 items: nn)*

[7]:
```
# Requirements
min_itemsets = 8
min_items_in_itemset = 2

# "Reasonable" range
support_range = np.arange(0.1, 0.01, -0.01)
```

[8]:
```
min_support = 0

for s_value in support_range:

    frequent_itemsets = apriori(basket, min_support = s_value, use_colnames =␣
↪True)

    # Calculate the number of itemsets that contain at least␣
↪`min_item_in_itemset` items
    itemsets_above_threshold = sum([len(itemset) >= min_items_in_itemset for␣
↪itemset in frequent_itemsets.itemsets])

    if itemsets_above_threshold >= min_itemsets:
        min_support = s_value
        break

print(f"min_support: {min_support:.4f} - number of itemsets with at least 2␣
↪items: {itemsets_above_threshold}")
```

```
min_support: 0.0500 - number of itemsets with at least 2 items: 9
```

1.7 6. find the minimum metric threshold such that at least 10 association rules are extracted from the frequent itemsets found (5 points)

- *use "confidence" as metric and output the line below:*
- *Metric: "confidence" - min_metric: 0.xxxx - Number of rules: n*

[9]:
```
# Threshold
min_rules = 10

# "Reasonable" range
confidence_range = np.arange(1, 0.01, -0.01)
```

[10]:
```
min_confidence = 0

for c_value in confidence_range:

    rules = association_rules(frequent_itemsets, metric = "confidence",␣
 ↪min_threshold = c_value)

    if len(rules) >= min_rules:
        min_confidence = c_value
        break

print(f'Metric: "confidence" - min_metric: {min_confidence:.4f} - Number of␣
 ↪rules: {len(rules)}')
```

```
Metric: "confidence" - min_metric: 0.2500 - Number of rules: 10
```

1.8 7. print the first 10 rules found, sorted by descending confidence and support (3 points)

[11]:
```
sorted_rules = rules.sort_values(by = ['confidence', 'support'], ascending =␣
 ↪False).reset_index(drop=True)
sorted_rules
```

[11]:

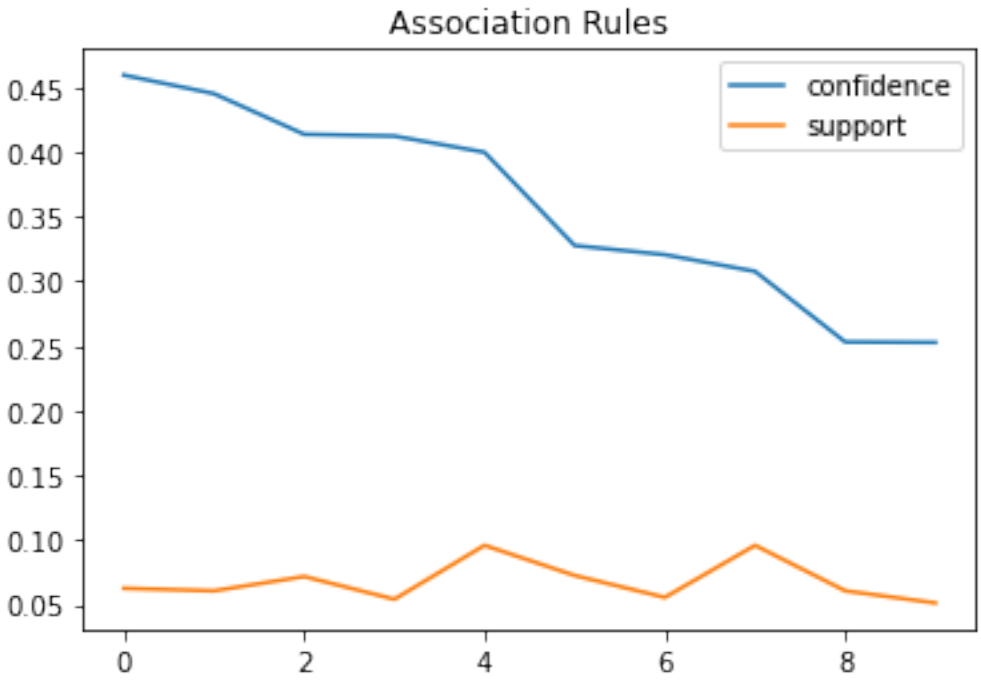
	antecedents	consequents	antecedent support	\
0	(root vegetables)	(whole milk)	0.136399	
1	(root vegetables)	(other vegetables)	0.136399	
2	(yogurt)	(whole milk)	0.173528	
3	(tropical fruit)	(whole milk)	0.131449	
4	(other vegetables)	(whole milk)	0.239838	
5	(rolls/buns)	(whole milk)	0.221470	
6	(yogurt)	(other vegetables)	0.173528	
7	(whole milk)	(other vegetables)	0.311621	
8	(other vegetables)	(root vegetables)	0.239838	
9	(soda)	(whole milk)	0.203101	

	consequent support	support	confidence	lift	leverage	conviction

0	0.311621	0.062663	0.459408	1.474254	0.020158	1.273380
1	0.239838	0.060709	0.445081	1.855754	0.027995	1.369861
2	0.311621	0.071782	0.413664	1.327459	0.017707	1.174035
3	0.311621	0.054195	0.412289	1.323049	0.013233	1.171290
4	0.311621	0.095883	0.399783	1.282915	0.021145	1.146884
5	0.311621	0.072564	0.327647	1.051429	0.003549	1.023836
6	0.239838	0.055628	0.320571	1.336610	0.014009	1.118823
7	0.239838	0.095883	0.307692	1.282915	0.021145	1.098011
8	0.136399	0.060709	0.253123	1.855754	0.027995	1.156283
9	0.311621	0.051329	0.252726	0.811006	-0.011962	0.921187

1.9 8. plot confidence and support for all the sorted rules found (3 points)

[12]:
```
sorted_rules[['confidence','support']].plot(title='Association Rules');
```



1.10 9. scatter plot the rules by confidence and support, labelling the points with the index value of the corresponding rule

[13]:
```
# Create a scatter plot of the sorted rules
fig = sorted_rules.plot.scatter(x = 'confidence', y = 'support', title =␣
↪'Association Rules');

# Iterate over all the rules and annotate them with their index
for i in range(len(sorted_rules)):
```

```
    fig.annotate(text = i, xy = (sorted_rules['confidence'][i],␣
↪sorted_rules['support'][i]))
```